Following the Leader? Network Models of "World Class" Universities on Twitter

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Much research on higher education has engaged with the concept of "world-class" universities and the complementary surge of interest in global university rankings. Literature takes a variety of positions on these intertwined phenomena, from vocal support of rankings and "world-class" aspirations to critical analyses of their influence and ideological underpinnings. Despite these differences, there is widespread consensus on the obsession with "world-class" status and the emergence of a new global field of competition (Altbach 2004; King, 2010; Robertson 2012; Tapper and Filippakoub, 2009). This field is disembedded from - but not entirely independent of - national systems of higher education and organized through rankings that create positional competition around research output and reputation (Marginson and van der Wende, 2007).

This paper seeks to understand how universities in global rankings relate to one another through social media as a way to better understand reputation and prestige in the field of "world-class" universities. Specifically, it examines the extent to which rankings are reflected in the structure of social media networks and whether those that occupy the top spaces in global rankings tend to associate with one another as a way of reproducing status. While social media networks are less academically focused than those of research collaboration (Moody, 2004) and less formal than institutional consortia (e.g. the World University Network and Universitas 21), they are highly visible, widely accessible and therefore a good measure of how institutions position themselves to maximise prestige within a globally competitive field. Social media are also an increasingly popular and influential means for public engagement and an important component of institutional branding.

The paper uses social network analysis and network modelling to examine universities' interactions on Twitter to study how relationships of prestige and positional competition operate in social media networks. Networks are conceptualised and operationalized at the institutional level, with a focus on how networks relate to institutions' reputation and prestige. It begins by discussing literature on "world-class" universities, global university rankings, and network perspectives on global higher education, and then introduces social network analysis, network modelling and sources of data. The analysis presents descriptive network statistics, data visualisations, and results of network models, and the paper concludes by discussing their significance for research on global higher education.

Literature Review: "World-Class" and "Network" Universities

Recent years have witnessed an obsession with "world-class" universities and global rankings, which can be traced to a steady growth in "world class" terminology since the turn of the century (Ramirez and Tiplic, 2014). Since then, creating "world-class" universities has become an obsession to the extent that "no country feels it can do without one" (Altbach, 2004).

The emergence of "world-class" phraseology has been coextensive with the rise of global university rankings. Global rankings are now published by many major media organizations, research centres and consultancies (e.g. Shanghai Jiao Tong, Thompson Reuters, etc). Researchers differ on their views of rankings, with some support (Liu and Cheng, 2005), calls for reform (Marginson, 2006; Taylor and Braddock, 2007), proposals for alternative methods (Guarino et al 2011; Jeremic et al, 2011), and much critique of their ideological underpinnings and consequences (Marginson, 2010). However, there is widespread agreement that global rankings are here to stay; in Marginson's (2006:132) words, they have become as "inevitable as death and taxes."

Both the "world-class" discourse and the ascendancy of global rankings have created a global higher education field (in Bourdieu's sense - Marginson, 2008) that is unbound from national contexts and geographical limitations. The result is a tendency to converge on a single model of the "world-class" university as a well-managed, rational actor that adheres to universal standards of excellence and quality (Ramirez, 2010). This model encapsulates a contradiction between national and global scales: while the necessity of the "world-class" university is couched in terms of national development and national economic competitiveness, its goals are expressed as extending beyond the confines of the nation state (Mohrman, Ma and Baker, 2008; Ramirez and Tiplic, 2014). However, this unipolar model of excellence is often at odds with contextual specifities, which result in a diversity of institutional enactments of global models (Paradeise and Thoenig, 2013).

The Network University

At the same time that the "world-class" discourse and global rankings have come to the fore of higher education literature, researchers have increasingly invoked the network as a conceptual device for understanding global trends in higher education. From a network perspective, the capacity of institutions and individuals derives largely from embeddedness in relationships of collaboration and flows of information (Granovetter, 1973). For example, a report from the British Royal Society claims that contemporary scientific research is driven by "self-organizing networks" that are "motivated by the bottom-up exchange of scientific insight, knowledge and skills, span the globe, and are changing the focus of science from the national to the global level" (Royal Society, 2011:62).

The resulting need to reconsider the organizational model of the university has led several authors to transpose Castells' (1996) concept of the "network society" to describe the "network university" (Lewis, Marginson and Snyder 2005; Grant, 2013). Reflecting the post-Fordist underpinnings of the "network society" in which flows of information drive economic production, the idealised "network university" is characterised by flexibility, non-hierarchical decision-making and deterritorialization, since geography and institutions no longer constrain academic work. However, Lewis, Marginson and Snyder (2005) point out that network organizations are not necessarily incompatible with authoritative bureaucracy and managerialism, concluding that the "the model of the flattened, networked university is still very much an ideal rather than a norm" (67). King (2010) concurs, arguing that network processes underpin the spread new public management strategies in higher education. In an inspiring an analysis, he goes on to show how "network power" - "the ability to coordinate multiple-linked actors" - drives institutional isomorphism and convergence on a model of the "world-class" university, as network power is translated into both normative and competitive pressures that constrain policymakers into "almost generic" prescriptions for institutions. (King, 2010:586-7).

While networks are well established as a conceptual device for understanding global higher education, empirical applications are more limited. Burris (2004) lays important groundwork in this respect, showing how networks of inter-institutional hiring (i.e. networks composed of institutions that hire PhD graduates from other institutions) are a better measure of academic prestige than output metrics such as publications and citations. Tapper and Filippakoub (2009) also identify that reputation is more complex and nuanced than ranking, and best understood as networks in which "members of a group reinforce each other's status" (62). This has important implications for how highly ranked universities associate with one another, as they explain

> Prestigious groupings would prefer to remain relatively small and impose strict entry conditions...It is possible that we are witnessing the steady growth of a global network of universities that are assumed to be world-class, and in the future this will be the network that carries the most prestige (Tapper and Filippakoub, 2009:61-2)

If true, then one would expect to see a clear relationship between rankings and how institutions associate with one another through social media, which are a highly visible form of prestige, as highly ranked institutions would form partnerships that preserve their elite status. To evaluate this proposition requires sophisticated methods of network analysis and modelling.

Methods and Data

Social Network Analysis and Network Models

Several decades of research on social networks have provided researchers with increasingly sophisticated tools to describe, visualise and analyse network data, resulting in what some have called a "network turn" in sociology (Beckfield, 2010:1020). Among the most important methodological developments in the field has been the definition of probabilistic models of network data. Building upon measures of network structure (e.g. reciprocity, centralization and clustering), network models allow researchers to test hypotheses about patterns in the relationships that form networks and analyse network data as an outcome of multiple associative processes.

Much work on network modelling has utilised exponential random graph models (ERGMs), a family of network models that explain the probability of an observed network as a function of both endogenous and exogenous variables (Robins et al, 2007, Snijders, 2011). The endogenous aspect of the model examines how structural relationships – those based on the presence or absence of other ties in the network – constitute and explain the formation of ties. For example, an endogenous analysis might examine the tendency of actors in the network to form relationships based upon mutual acquaintances or to create ties reciprocally. In contrast, the exogenous component of the model examines how external variables – those outside the relationships that constitute the network - are related to network structure, for example, whether actors that share common traits are more likely to associate with one another. In the context of this analysis, these traits include variables related to institutions' ranking and location.

ERGMs have proven a very successful approach to modelling many types of networks (Robins and Lusher, 2013a; Desmarais and Cranmer, 2012), largely because they simultaneously account for endogenous and exogenous variables that explain the probability of a tie, controlling for their respective influence. For example, some of the probability of a tie may be explained by structural factors such as mutual connections or reciprocity, while some may be due to external factors such similarity between actors. Given sufficient data, ERGMs are able to disaggregate these two influences. Finally, ERGMs produce a familiar output similar to that of logistic regression (Koskinen and Daraganova, 2013), a set of coefficients that express the change in the probability of a tie associated with a change in each independent variable, along with confidence intervals and significance levels. However, the assumptions regarding dependency of in ERGMSs are much more complex than other approaches to linear modelling, in which the independence of observations is assumed, or dependencies are accounted for through robust standard errors (Hayes and Cai, 2007) or multilevel approaches (Goldstein, 1995). In contrast, a fundamental assumption of ERGMS is the dependency of links: measurements of network structure are premised on the notion that the presence of one tie is related to the rest of the network structure. ERGMs model dependency through a computationally-intensive process of Markov Chain Monte Carlo (MCMC) parameter estimation (Koskinen and Snijders, 2013).

Data Sources

The data used in the analysis were collected from the Twitter accounts of universities that appear in the most recent edition of four prominent world university rankings: the Times Higher Education World University Rankings, the Quacquarelli Symonds' (QS) World University Rankings, Shanghai Jiao Tong University's Academic Ranking of World Universities and US News and World Report's Top World Universities. Any institution that appeared in at least two of the four rankings was included in the study, yielding an initial sample of 221 universities. The rankings data were used to compute a prestige score for each institution based on its average score in each of the rankings. Thus, in the context of this paper, rankings are operationalized as links between institutions at a central level, although it is also recognized that networks exist at other levels (e.g. between individuals and departments) and in other domains (e.g. research collaboration).

Twitter was selected as the primary source of data because of its widespread use, relative simplicity, and public visibility. Started in 2006, Twitter allows registered users to communicate through short messages known as tweets. Twitter users are able to "follow" others on the site, meaning that they receive notifications of their tweets; following another user signifies that they communicate useful, relevant or interesting information. The initial sample of 221 universities was identified with Twitter accounts that serve the institution as a whole; these central accounts include news outlets and press offices, but exclude accounts for specific faculties and departments or organisational units such as the international office, students' union, research centres, or athletics. In cases where the university maintained bilingual central Twitter accounts (one in English and one in the national/regional language), both accounts were included in the sample. The sample therefore focuses on institutions, particularly social media activity that is centrally managed and occurs between institutions. This approach precludes insight into communication within institutions and lower-level communication between institutions, but focuses on publicly visible, centralised interactions that relate to an institution's public profile, reputation and status. In total, 211 of the universities were identified with a central Twitter account that met the specified criteria.

Data on users' following and tweets were obtained through the Twitter Application Programming Interface (API), which provides a standardised mechansim for software access to Twitter data. Data were collected on 28 - 30 November, 2013 and included raw data on 276,133 followers and 137,680 tweets. This data was used to compile three types of network datasets:

> Followers: A network of universities that follow one another. This provides data on valued sources of information and determines the paths through which information can flow across the network. An institution is connected to all other institutions it follows on Twitter.
>
> Hashtags: A network of universities that tweet on the same topic. Hashtags are keywords identified with a "#" sign to label the content of the tweet (e.g. the hashtag "#innovation" labels a tweet as relevant to innovation). Shared hashtags represent participation in the same conversation, but not necessarily direct connection or interaction between institutions. Two institutions are connected in the hashtags network if they used a common hashtag in their tweets.
>
> Mentions: A network of other universities that were directly mentioned in an institution's communications by prefacing the university's Twitter ID with the "@" sign. An institution is tied to all other institutions it mentioned in its tweets.

The followers and mentions networks' ties are directed, which mean that connections are not necessarily symmetrical. For example, given two hypothetical universities A and B, it is possible that A follows or mentions B, but that B does not follow or mention A. Such asymmetrical ties can provide insight into relative prestige and hierarchies in network structure (Wasserman and Faust, 1994). In contrast, the hashtags network is symmetrical: two universities share are connected if they tweeted on the same hashtag with no directionality involved. The directed followers and mentions networks each contain 44,310 possible ties, while the undirected hashtag network contains 22,155 possible ties.

The precise meaning of network ties – and by extension the larger network they constitute – is somewhat ambiguous and open to interpretation (Marsden, 2005). Activity on Twitter reflects decisions made by numerous individuals with different interests and responsibilities in each institution. Although the analysis focuses on centrally managed accounts, such decisions are unlikely to reflect a formal strategic position but are better considered a sign that another institution is a valued source of information (in the case of following), a logical peer, collaborator or partner (in the case of mentions) or that institutions share common interests (in the case of hashtags). However, it is not a claim of the study that the meaning of such ties is uniform and concrete, only that when aggregated they provide insight into patterns of communication between institutions. A useful counterpoint to the ambiguity of ties is that they are clearly non-random nature, a fact that is evident in the analysis and visualisations presented below. The analysis is structured in two parts: the first presents descriptive network statistics and visualisations, and the second presents and interprets results of ERGMs of network data.

Analysis

Network Visualisations and Structure

Before modelling network data, visualisations and measures of network structure provide a useful overview of the data. Two visualisations of the followers network are given in Figures 1 and 2 (visualisations of other networks are presented in the electronic supplement). Both figures highlight the complexity of social media networks, but also show that rankings and geography appear to be related to network structure. In Figure 1, highly ranked institutions (those with larger markers) tend to be more central, meaning they have ties to a relatively large number of other institutions. Additionally, there is some clustering of universities by regional location, which is represented through different marker shapes. Figure 2 demonstrates the latter relationship by plotting ties on a world map.

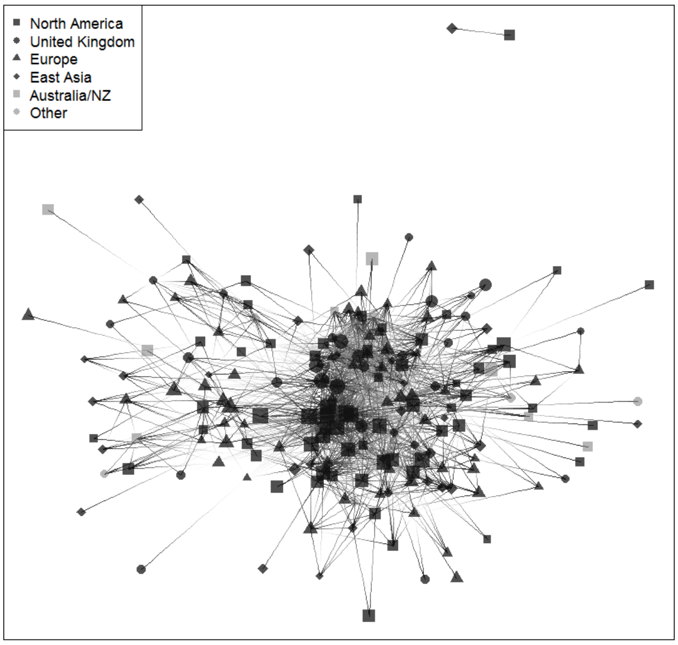

FIGURE 1: The followers network, plotted using the force-directed plotting algorithm described by Fruchterman and Reingold (1991). Actors are represented by points, with larger points indicating a higher ranking and marker shape denoting geographic region. Ties are drawn with using a gradient line, which is lighter and more transparent near the follower and darker and more opaque near the followed actor. 15 isolates (unconnected actors) have been removed to improve clarity.

FIGURE 2: The followers network, plotted geographically. Ties are drawn with using a gradient line, which is lighter and more transparent near the follower and darker and more opaque near the followed actor.

Measures of key structural properties of the networks are presented in Table 1. The first measure, density, is simply the number of ties present in the network as a proportion of all possible ties. A network with no connected actors would have a density of zero, and a network in which all actors were connected to one another would have a density of one. The hashtags network is the densest of the three, followed by followers and then mentions. Since tweeting on a common hashtag is a relatively weak form interaction with no direct communication, it is not surprising that this network has the highest density. Next, reciprocity measures the proportion of ties in the network that are reciprocal; lower levels of reciprocity correspond to more asymmetrical network structures. Reciprocity does not apply to the hashtag network, as ties are not directed, but results show that the followers and mentions network are highly symmetrical. Third, transitivity measures the extent to which mutual connections influence network ties. A tie is transitive if it connects two actors who share a mutual connection. The measure of transitivity is simply the proportion of transitive ties relative to all possible combinations of actors (Wasserman and Faust, 1994).

	Followers		Hashtags		Mentions	
Network Composition						
Type	Directed		Undirected		Directed	
Actors	211		211		211	
Ties	2001		9986		201	
Isolates	15		39		69	
Structural Measures	Value	T-value	Value	T-Value	Value	T-Value
Density	0.045		0.225		0.002	
Reciprocity	0.947	17.724	--	--	0.998	2.53
Transitivity	0.453	202.97	0.646	128.76	0.18	20.284
Degree Centralization	0.219	38.764	0.45	28.66	0.02	7.886
Eigenvector Centralization	0.231	14.317	0.113	13.98	0.572	-0.647

TABLE 1: Network composition and structural measures for the three networks. T-values measure the observed value in relation to the mean and standard deviation of a sample of 100 random networks with equivalent density of ties. Density scores do not have a t-value as observed values were used to simulate networks.

Centralization measures the inequality in actors' centrality across a network; higher levels of network centralization indicate that the network exhibits a stronger core-periphery structure (Wasserman and Faust, 1994). Centrality itself can be defined using a variety of different measures, two of which - degree and eigenvector centrality – are reported in Table 1. The first measure - degree centrality - is simply the number of incoming links for each actor in the network, or in the case of the undirected hashtags network the total number of connections to each actor. In contrast, the more complex measure of eigenvector centrality weights incoming ties according to the sender's own centrality. Thus, being followed by a university that is widely followed itself represents a greater level of centrality than being followed by one with few followers of its own. Because of this property, Burris links eigenvector centralization to Bourdieu's notion of social capital, which is premised on the idea that "not all connections are of equal value" (Burris, 2004:251). Algorithms based on eigenvectors are also used in internet search engines and measuring the impact of academic journals (Bryan and Leise, 2006; Bergstrom, West and Wiseman, 2008).

A problem with assessing network structure is that all relationships are present to some extent due to chance alone. For example, a very dense network would contain many transitive and reciprocal ties because such structures would be inevitable given the density of the network. For this reason, each structural measurement in Table 1 is paired with a t-statistic that measures the observed value of the measure in standard deviations relative to a sample of 100 random networks with the same density of ties, a technique known as conditional uniform testing (Wasserman and Faust, 1996:535). Given a critical t-value of 1.98, most structural measures are highly significant, indicating these structural features are not due to chance alone. Overall, visualisations and structural measures give evidence of multiple endogenous and exogenous factors that influence network relationships: visualisations show that ranking and geography appear to be important factors in higher education Twitter networks. Structural factors such as reciprocity and transitivity also appear highly influential in the formation of ties. Both of these propositions can be tested through ERGMs.

Network Models

Based on the literature review, visualisations and preliminary analysis, network models examine whether universities seek to preserve their elite status on Twitter through mutual associations and investigate the influence of geographical factors and structural relationships (e.g. reciprocal and transitive ties) on tie formation. These relationships were investigated through a series of models on each network presented in Tables 2 and 3. Models were fit using the ERGM library for the R statistical programming language (Handcock et al, 2013; Hunter et al, 2008, R Core Team, 2013).

Model 1 presents a relatively simple test of the influence of rankings on network structure: in addition to endogenous model terms for transitivity and reciprocity, the receiver's ranking score is included as an exogenous covariate, modelling whether highly-ranked institutions are likely to receive more followers or mentions. The first model term – edges – indicates the probability of a tie – expressed as a logarithmically scaled odds ratio – when all other covariates are zero, akin to an intercept term in regression analysis (further guidance on interpreting output coefficients is given in the electronic supplement). In the undirected hashtags network, ties are symmetrical; therefore, it is not possible to identify a receiver effect for rankings. Results show that there is a significant effect associated with ranking in both the followers and mentions network; however, the size of this effect is much smaller than those associated with the endogenous relationships. For example, a one standard deviation increase in an institution's ranking score (15.02 points) would correspond to a 0.045 increase (15.02 x 0.003) in the log-odds of a tie in the followers network. In contrast, a tie that results in a reciprocal link or closes a transitive triad is far more likely, increasing the log-odds by 2.35 and 1.22, respectively.

Model 2 examines the relationship between network structure and ranking from a different perspective: rather than the receiver's ranking, the sum prestige of both actors is used as a predictor of tie formation. While Model 1 tests whether highly ranked institutions are more likely to be followed, Model 2 examines whether highly ranked institutions associate with one another. The ranking term is significant in both the followers and mentions networks; however the effect size is smaller than in Model 1. Also, the Bayesian Information Criterion (BIC) - a measure of network fit - has increased for these networks, indicating that Model 2 does not fit observed data as well as Model 1. While there is a slight tendency for highly ranked institutions to associate with one another, results suggest the effect of ranking is mainly based on the receiver. However, for the hashtags network, there is no significant relationship between ranking and network ties; therefore it appears that highly ranked universities are no more likely to tweet on the same topics than other institutions.

	Model 1		Model 2		
	Followers	Mentions	Followers	Hashtags	Mentions
Endogenous Parameters					
Edges	-6.63 (0.20)**	-10.80 (0.32)**	-5.34 (0.15)**	-3.93(0.41)**	-10.45(0.33)**
Reciprocity	2.35 (0.11)**	5.45 (0.06)**	2.19 (0.05)**		4.87(0.11)**
Transitivity	1.22 (0.08)**	2.11 (0.22)**	1.25 (0.08)**	0.10(0.00)**	1.89(0.19)**
Isolates					
Exogenous Parameters					
Ranking - Receiver Effect	0.02 (0.00)**	0.05 (0.00)**			
Ranking - Dyad Effect			0.003 (0.00)**	-0.004 (0.00)	0.03 (0.00)**
Goodness of Fit					
AIC	12,436	880	12584	23372	887
BIC	12,471	915	12619	23396	922

TABLE 2: Results from Models 1 and 2: the former uses the receiver's ranking as a predictor of tie formation, while the latter uses the sender and receiver's combined ranking. Coefficients are displayed up to two decimal places, except for those less than 0.01, which are displayed to three places.

	Model 3			Model 4		
	Followers	Hashtags	Mentions	Followers	Hashtags	Mentions
Endogenous Parameters						
Edges	-6.12 (0.22)**	-4.08 (0.66)**	-8.94 (0.32)**	-6.04 (0.15)**	-3.33 (0.00)**	-8.01 (0.19)**
Reciprocity	1.59 (0.14)**		3.68 (0.14)**	1.61 (0.09)**		3.43 (0.06)**
Transitivity	1.33 (0.06)**	0.11 (0.00)**	1.94 (0.19)**	1.51 (0.08)**	0.10 (0.00)**	1.41 (0.10)**
Isolates					4.09 (0.00)**	1.80 (0.90)**
Exogenous Parameters						
Ranking – (Receiver)	0.01 (0.00)**		0.03 (0.003)**	0.01 (0.00)**		
Ranking – (Dyad)		0.001 (0.00)				
Nation-State Match	0.73 (0.09)**	0.14 (0.40)	-1.01 (0.67)*	0.33(0.06)**		
Region Match	0.20 (0.09)*	0.58 (0.47)	2.84 (0.68)**	0.25 (0.06)**		0.03 (0.00)**
Distance (1,000 km)	-0.03 (0.01)**	0.35 (0.25)	-0.06 (0.02)**	-0.03 (0.01)**	0.38 (0.00)**	1.38 (0.03)**
English-Speaking	0.017 (0.08)	-0.07 (0.04)$^{+}$	0.013 (0.30)		-0.06 (0.00)**	
Goodness of Fit						
AIC	11,483	17,727	813	11,422	17,282	825
BIC	11,553	17,783	883	11,482	17,322	877

TABLE 3: Results for Models 3 and 4, which include several geographic variables.

Model 3 extends Models 1 and 2 by including several terms to measure geographical influences on tie formation and adopting receiver effects as the best approach to modelling ranking (except for the hashtags network in which ties are symmetrical and the combined ranking score is retained from Model 2). First, the model adds a term to test whether institutions in the same nation-state are more likely to form a tie with one another. Second, geographic region is used to test whether institutions tend to form ties with institutions in nearby countries (using the same method of classification as Figure 1). Third, the geospatial distance between institutions (measured in thousands of kilometers - Wallace, 2012), is used as a dyadic covariate to determine whether institutions physically closer to one another (regardless of national borders) are more likely to form ties. This term is important since physical distances and national borders can be very different from one another: for example, universities in the United States might associate with one another across large distances without any international links, while interaction between institutions at similar distances in Europe would cross several national boundaries. Controlling for geospatial distance isolates the effect of borders from the underlying physical distance. Finally, the model draws upon work that identifies the importance of five key English-speaking countries in global higher education (the USA, UK, New Zealand, Canada and Australia – Böhm et al, 2004), to test whether the predominance of English is more important than national, regional, or geospatial effects.

Across all three networks, incorporation of geographic terms improves the model fit, indicated in decreased BIC values. In the followers and mentions network, geography is significantly related to tie-formation: institutions in the same nation-state and geographic region are more likely to follow one another. These effects are moderately large: for example, in the followers network, location in the same nation-state increases the log-odds of tie formation by approximately the same amount as a 60 point increase in the composite ranking score ($0.731 \approx 0.012 \times 60$). However, in both the followers and mentions networks, geographic effects are smaller than those associated with reciprocal ties. Additionally, the distance effect for the followers networks is significant and negative, indicating that the probability of a tie decreases with greater distance. Thus, despite the instantaneous global connectivity offered by social media, the network is not entirely deterritorialized as physical distance does influence interaction. While the model fit is improved for the hashtags network, geographic terms are not significant. Near-significant terms (English-language and geospatial distance) are used to create an improved final model specification for hashtags in Model 4.

Model 4 provides a final specification that best captures the probability of tie formation for each network. For the followers network, the non-significant English speaking term is dropped, resulting in an improved model fit as indicated by the lower BIC value. The final hashtag model drops non-significant terms for ranking, nation-state and region but retains terms for geospatial distance and English speaking countries. As a result, all model terms are significant and the overall model fit is improved. While multiple geographic terms were non-significant for the hashtag network in Model 3, the single simplified geospatial distance term is significant. Unlike the other two models, countries in English-speaking institutions are more likely to be connected in the hashtags network, which is logical given that the hashtags network is most closely related to the content (and therefore the language) of tweets. Finally, the non-significant nation-state and English-speaking terms are removed from the mentions network and an endogenous term is added for isolates - institutions that are completely unconnected - due to the very low density of network connections. As with the other networks, this results in an improvement to the overall model fit.

Following the final network specification, diagnostic and evaluation procedures were used to determine goodness of fit. Evaluating goodness of fit for ERGMs involves simulating a network dataset using the fit model parameters (i.e. using the coefficients for Model 4 to generate new network data) and comparing the structure of simulated and original data (Robins and Lusher, 2013b). Table 4 presents structural measures of simulated networks with comparisons to the original data in Table 1; it is worth noting that not all structural measures presented in the table were included in the network models, explaining some of the differences in centralization measures. However, the structural properties of simulated networks are reasonably close to the original data, meaning that the models are a faithful reduction; nothing in diagnostic procedures undermines the validity of the analysis as a whole.

	Followers		Hashtags		Mentions	
	Obs.	Sim.	Obs.	Sim.	Obs.	Sim.
Density	0.05	0.04 (0.00)	0.23	0.23 (0.00)	0.002	0.001 (0.00)
Reciprocity	0.95	0.96 (0.00)	--	--	1.00	1.00 (0.00)
Isolates	15	10.58 (3.37)	39	36.50 (1.04)	69	156.95 (8.63)
Transitivity	0.45	0.23 (0.01)	0.65	0.67 (0.00)	0.18	0.22 (0.07)
Centralization						
Degree	0.22	0.16 (0.01)	0.45	0.37 (0.01)	0.02	0.02 (0.00)
Eigenvector	0.23	0.19 (0.01)	0.11	0.07 (0.00)	0.57	0.51 (0.07)

TABLE 4: Results from network simulations based on the results of Model 4. Observed values are from the network data (see Table 1), simulated values are based on a sample of 100 simulated networks using the parameters of Model 4. Mean values of the sample are presented, with standard deviations in parentheses.

Analysis Summary

Overall, the models demonstrate how structural factors, ranking and geographic considerations influence connectivity between institutions and give rise to the global social media network between "world-class" universities. Because of the technical nature of statistical modelling, it may be helpful to summarise the main findings of network models as follows:

1. Ranking has a statistically significant relationship to tie formation, but the size of its effect is quite small. The ranking of an institution increases the likelihood it will be followed or mentioned on Twitter.

2. Geographical factors are also significantly related to the probability of tie formation. Institutions located in the same nation-state or geographic region are more likely to be connected to one another, and the size of this effect is larger than ranking.

3. The strongest predictors of tie formation are structural: a tie is most likely to be formed if it would reciprocate an existing tie or it is related to a mutual acquaintance.

Thus, while there is evidence that rankings influence how institutions interact through social media, they do not appear to play a decisive role in shaping social media networks between "world class" universities. Rather, the structural influences and bordered geography (i.e. the effect of national and regional groupings controlling for underlying physical distance) appear to have most influence on and network structure.

Discussion

The analysis demonstrates that ERGMs are a useful approach to capturing key aspects of network structure and explaining the global structure of networks through local processes of tie formation. However, interpreting the significance of the models with respect to the context of "world-class" universities and global rankings is more challenging and requires a return to the conceptual issues raised in the literature review. This section presents two possible interpretations of the network models presented above.

One way to interpret findings is to accept the "world-class" category and to interpret its network of social media connections. From this perspective, the study is concerned with social media communication among a fixed group of actors, and results shows universities communicate through social media for reasons that are less related to status competition than geographic and structural factors. Thus, this interpretation accepts the primacy of the "world-class" category and uses it to analyse social media networks, which are shown to be more localized and less driven by status competition than the global field.

A second approach to interpretation is to use the observed social media networks to critically interrogate the logic of the "world-class" category. In other words, this interpretation asserts the primacy of observed social media networks and analyzes the "boundary specifications" (Wasserman and Faust, 1994) of actors that constitute the network. From this perspective, the importance of national and regional boundaries and minimal influence of rankings suggest that field of global higher education is not as unitary and cohesive as the "world-class" label and associated global rankings imply (Paradeise and Thoenig, 2013). Rather than measuring an existing category of institutions, "world-class" institutions are talked into being through global rankings. This interpretation is very much compatible with Robertson's (2012) assertion that the "world-class" discourse is a "project" in which power is mobilized through the authority to rank institutions and induce competition. However, it also gives good reason for optimism as results show that when communicating through social media, positional competition and status are relatively unimportant, leaving space for meaningful communications between institutions on shared interests.

Ultimately, more research is needed to mediate between these two perspectives, but the analysis presented here is sufficient to question the extent to which rankings organize the field of global higher education and to add weight to research questioning their practical significance (Souto-Otero, Forthcoming). Network models of other higher education networks (e.g. research collaboration and institutional consortia) may provide further insight into the cohesiveness of the "world-class" category and how rankings influence relationships between institutions.

While these two interpretations differ in their views of "world-class" universities, they both identify the importance of national and regional boundaries in shaping the structure of social media networks. The role of the state in the globalization of higher education has been discussed by others; for example, Marginson and van der Wende acknowledge that universities are increasingly "disembedded' from their national contexts," but also caution that the "degree of separation from the nation should not be overstated" (Marginson and van der Wende, 2007:29, 15). Enders (2004:364) also points out that although the medieval university was international (to the extent that nation-states could be said to exist), "the contemporary university was born of the nation state." More recently, research has identified regionalization - coordinated policymaking by groups of nation-states - as a key driving force in the globalization of higher education (Dale and Robertson, 2002; Author). The analysis presented here shows that although fluid and self-organizing flows of social media communication are not constrained by distance or borders, social media networks tend to reproduce borders as much as they remove them. Contemporary global education is far from "borderless;" hence, any analysis of "world-class" universities and global rankings must also take into account the co-constitutive relationship between bounded territories – both national and regional – and competition on a global scale.

References

Altbach, P. G. (2004). The costs and benefits of world-class universities. *Academe*, 90(1), 20-23.

Bergstrom, C.T., West, J.D. & Wiseman, M.A. (2008). The eigenfactor metrics. *Journal of Neuroscience* 28(45), 11433-11434

Böhm, A., Follari, M. Hewett, A. Jones, S., Kemp, N., Meares, D., Pearce, D. & can Caute, K. (2004). *Vision 2020, Forecasting International Student Mobility: A UK Perspective*. London: British Council.

Burris, V. (2004). The academic caste system: Prestige hierarchies in PhD exchange networks. *American Sociological Review*, 69(2), 239-64.

Bryan, K. & Leise, T. (2006).The $25,000,000,000 eigenvector: The linear algebra behind Google. *Society for Industrial and Applied Mathematics Review*, 48(3), 569-581.

Castells, M. (1996). *The Rise of the Network Society*. Oxford: Blackwell Publishers Limited.

Dale, R. & Robertson, S.L. (2002). The varying effects of regional organizations as subjects of globalization of education. *Comparative Education Review*, 46(2), 10-36. DOI: 10.1086/324052

Desmarais, B.A. & Cranmer, S.J. (2012). Statistical inference for valued-edge networks: The generalized exponential random graph model. *PLoS ONE*, 7(1).

Enders, J. (2004). Higher education, internationalisation, and the nation-state: recent developments and challenges for governance theory. *Higher Education*, 47(3), 361-382. DOI:10.1023/B:HIGH.0000016461.98676.30

Grant, C.B. (2013) Losing our chains? Contexts and ethics of university internationalisation. Leadership Foundation for Higher Education Stimulus Paper. ISBN: 978-1-906627-42-3

Handcock, M., Hunter, D., Butts, C., Goodreau, S., Krivitsky, P. & Morris, M. (2013). ERGM: Fit, simulate and diagnose exponential-family models for networks. R package version 3.1.1, CRAN.R-project.org/package=ergm.

Hunter D.R., Handcock, M.S., Butts, C.T., Goodreau, S.M, & Morris, M. (2008). ERGM: A package to fit, simulate and diagnose exponential-family models for networks. Journal of Statistical Software,24(3), 1-29.

Jeremic, V. Bulajic, M., Martic, M. & Radojicic, Z. (2011). A fresh approach to evaluating the academic ranking of world universities. *Scientometrics*, 87(3), 587-596.

Jobbins, David. (2005) Moving to a Global Stage: A Media View, *Higher Education in Europe*, 30:2, 137-145

Liu, N.C. & Cheng, Y. (2005). The academic ranking of world universities. *Higher Education in Europe*, 30(2), 127-136.

Fruchterman, T. M. J. & Reingold, E. M. (1991). Graph drawing by force-directed placement. *Software: Practice and Experience*, 21(11), 1129–1164. doi: 10.1002/spe.4380211102

Guarino, C., Ridgeway, G., Chun, M. & Buddin, R. (2011). Latent variable analysis: A new approach to university ranking. *Higher Education in Europe*, 30:2, 147-165,

Goldstein, H. (1995). *Multilevel Statistical Models*. Chichester: Wiley.

Granovetter, M. (1973). The strength of weak ties. *American Journal of Sociology,* 78(6), 1360-1380.

Hayes, A.F. & Cai, L. (2007). Using heteroskedasticity-consistent standard error estimators in OLS regression: An introduction and software implementation. *Behaviour Research Methods*, 39(4), 709-22.

King, R. (2010). Policy internationalization, national variety and governance: global models and network power in higher education states. *Higher Education*, 60, 583-594.

Koskinen, J. & Daraganova, G. (2013). Exponential random graph model fundamentals. In D. Lusher, J. Kokinen & G. Robins (eds), *Exponential Random Graph Models for Social Networks: Theory, Methods and Applications*. Cambridge: Cambridge University Press, pp. 49 - 76.

Koskinen, J. & Snijders, T. (2013). Simulation, estimation and goodness of fit. In D. Lusher, J. Kokinen & G. Robins (eds), *Exponential Random Graph Models for Social Networks: Theory, Methods and Applications*. Cambridge: Cambridge University Press, pp. 141 - 166.

Lewis, T., Marginson, S. and Synder, I. (2005). The network university? Technology, culture and organisational complexity in contemporary higher education. *Higher Education Quarterly*, 59(1), 56-75.

Marginson, S. (2006). Dynamics of national and global competition in higher education. *Higher Education*, 52, 1-39.

Marginson, S. & van der Wende, M. (2007). Globalisation and higher education. Education working paper number 8. EDU/WKP(2007)3. Paris: Organisation for Economic Co-operation and Development.

Marginson, S. (2008). Global field and global imagining: Bourdieu and worldwide higher education. *British Journal of Sociology of Education*, 29(3), 303-315.

Marginson, S. (2010). Global comparisons and the university knowledge economy. In L.M. Portnoi, V.D. Rust and S.S. Bagley (eds), *Higher Education, Policy and the Global Competition Phenomenon*. New York: Palgrave Macmillan, pp. 29-42.

Marsden, P.V. (2005). Recent developments in network measurement. In S. Wasserman (ed), *Models and Methods in Social Network Analysis*, Cambridge: Cambridge University Press, pp. 8-30.

Mohrman, K., Ma, W. & Baker, D. (2008). The research university in transition: The emerging global model. *Higher Education Policy*, 21, 5–27.

Moody, J. (2004). The Structure of a social science collaboration network: Disciplinary cohesion from 1963 to 1999. *American Sociological Review*, 69(2), 213-238.

Paradeise, C. and Thoenig, J-C. (2013). Academic institutions in search of quality: Local orders and global standards. *Organization Studies*, 34(2), 189-218.

R Core Team (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org/.

Ramirez, F.O. (2010). Accounting for excellence: Transforming universities into organizational actors. In L.M. Portnoi, V.D. Rust and S.S. Bagley (eds), *Higher Education, Policy and the Global Competition Phenomenon*. New York: Palgrave Macmillan, pp. 43-58.

Ramirez, F.O. & Tiplic, D. (2014). In pursuit of excellence? Discursive patterns in European higher education research. *Higher Education*, Volume 67, Issue 4, 439-455 doi:10.1007/s10734-013-9681-1.

Robertson, S.L. (2012). World-class higher education (for whom?). *Prospects*, 42(3), 237-45.

Robins, G., Pattison, P., Kalish, Y. & Lusher., D. (2007). An Introduction to Exponential Random Graph Models(p*) for Social Networks. *Social Networks*, 29(2), 173-191.

Robins, G. & Lusher, D. (2013a).What are exponential random graph models? In D. Lusher, J. Kokinen & G. Robins (eds), *Exponential Random Graph Models for Social Networks: Theory, Methods and Applications*. Cambridge: Cambridge University Press, pp. 9 - 15.

Robins, G. & Lusher, D. (2013b). Illustrations: Simulation, estimation and goodness of fit. In D. Lusher, J. Kokinen & G. Robins (eds), *Exponential Random Graph Models for Social Networks: Theory, Methods and Applications*. Cambridge: Cambridge University Press, pp. 167 - 185.

Royal Society. (2011). *Knowledge, networks and nations: Global scientific collaboration in the 21st century*. ISBN: 978-0-85403-890-9.

Snijders, T. (2011). Statistical models for social networks. *Annual Review of Sociology*, 37, 131-153.

Souto-Otero. Forthcoming. Global higher education rankings and the meritocratic paranoia. Under review.

Tapper, T. & Filippakoub, O. (2009). The world-class league tables and the sustaining of international reputations in higher education. *Journal of Higher Education Policy and Management*, 31(1), 55-66.

Taylor, P. & Braddock, R. (2007). International university ranking systems and the idea of university excellence. *Journal of Higher Education Policy and Management*, 29:3, 245-260.

Wasserman, S. & Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Cambridge: Cambridge University Press.

Wallace, J.R. (2012). Imap: Interactive Mapping. R package version 1.32. http://CRAN.R-project.org/package=Imap